

**SMARTROSE: AI-IOT PLATFORM FOR SMART  
GREENHOUSE ROSE FARMING IN SRI LANKA**

25-26J-299

Final Thesis

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**B.Sc. (Hons) Degree in Information Technology Specialized in Information  
Technology**

**Department of Information Technology**

**Sri Lanka Institute of Information Technology**

**Sri Lanka**

**August 2025**

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# DECLARATION

## **ABSTRACT**

Middle-scale rose cultivation plays a significant role in the agricultural sector of countries like Sri Lanka, contributing to both local markets and export income. However, farmers in this sector often face challenges due to the lack of timely identification of plant diseases, which leads to reduced yield, economic losses, and inefficient use of resources. The current practices in disease detection are largely manual, time-consuming, and dependent on farmers' experience, making early detection difficult.

This research focuses on developing an Early Disease Alerting System tailored for rose cultivation, aiming to address the limitations in existing disease monitoring methods. The key problem identified is the absence of an automated, accurate, and real-time mechanism to detect early signs of diseases in rose plants under varying environmental conditions.

The proposed system utilizes data such as plant conditions, environmental factors, and historical disease patterns to analyze and predict potential disease outbreaks. By applying data processing techniques and predictive algorithms, the system generates timely alerts, enabling farmers to take preventive actions before the disease spreads.

This approach enhances decision-making, minimizes crop damage, and improves overall productivity in middle-scale rose cultivation. Ultimately, the system demonstrates how technology-driven solutions can effectively support sustainable agriculture and reduce risks associated with plant diseases.

**Keywords:** Early Disease Detection, Rose Cultivation, Smart Agriculture, Internet of Things (IoT), Environmental Monitoring, Temperature Difference ( $\Delta T$ ), Machine Learning, Random Forest Classifier, Real-Time Alerting System, Greenhouse Monitoring, Plant Health Classification, Sensor-Based System, Precision Agriculture, Predictive Analytics, Mobile Application

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## LIST OF ABBREVIATIONS

<b>Abbreviation</b>	<b>Description</b>
IoT	Internet of Things
ML	Machine Learning
AI	Artificial Intelligence
RF	Random Forest
CNN	Convolutional Neural Network
$\Delta T$	Temperature Difference
ESP32	Microcontroller Unit
SHT31	Temperature and Humidity Sensor
MLX90614	Infrared Temperature Sensor

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# 1. INTRODUCTION

## 1.1. Background and Literature Review

Rose (*Rosa hybrida* L.), widely known as the “Queen of the flowers,” is one of the most economically and aesthetically significant crops in the global floriculture industry [1]. In Sri Lanka, rose cultivation is practiced at small to medium scales, primarily in upcountry regions where climatic conditions such as lower temperatures are more favorable for plant growth [2]. However, due to the tropical nature of the country, rose cultivation faces significant environmental challenges, particularly in mid- and low-country regions where temperatures typically range between 24°C and 28°C. These conditions negatively affect plant growth, reduce flower quality, and increase susceptibility to diseases [2], [3]. To mitigate these issues, farmers adopt greenhouse cultivation techniques using shade nets, misting systems, and air-drying mechanisms to regulate environmental conditions. Despite these efforts, most greenhouse systems rely on manual monitoring, making them inefficient in responding to rapid environmental changes.

A real-world case study involving a middle-scale Sri Lankan rose farmer further highlights these challenges. The farmer had discontinued rose cultivation due to the uncontrolled spread of diseases across flower beds, despite using imported rose varieties, fertilizers, misting technologies, and air-drying systems. The primary issue was the inability to identify early-stage disease conditions and environmental fluctuations within the greenhouse. The farmer relied on periodic manual inspection to determine temperature changes and decide whether to apply misting or drying, but such decisions were often delayed, allowing diseases to spread rapidly. This scenario demonstrates the critical need for continuous monitoring and early detection mechanisms in rose cultivation.

Existing literature emphasizes that environmental factors such as temperature, humidity, and light intensity play a crucial role in plant growth and disease development. Rupasinghe et al. [2] demonstrated that optimal shading conditions (25%) significantly improve flower yield and quality in greenhouse environments, while excessive shading reduces productivity. Similarly, studies on rose diseases indicate that pathogens, particularly fungi, thrive under specific environmental conditions such as high humidity and prolonged leaf wetness, enabling rapid disease spread [3], [4]. Traditional disease identification methods are primarily based on visual inspection of symptoms such as leaf discoloration, spots, and

deformation, which often occur after the disease has already progressed [4]. In severe cases, such as Rose Rosette Disease, infections can spread systemically and lead to complete plant loss, highlighting the importance of early detection and prevention [5].

Recent advancements in technology have introduced automated disease detection systems using image processing and machine learning techniques. These systems typically involve image acquisition, preprocessing, feature extraction, and classification using models such as Support Vector Machines and Convolutional Neural Networks [6]. Deep learning approaches have achieved high accuracy in classifying plant diseases, with models such as MobileNetV2 and VGG16 demonstrating performance exceeding 90% [7]. Furthermore, advanced techniques such as lightweight object detection models and knowledge distillation frameworks have been developed to improve real-time detection in field environments [8]. However, despite their high accuracy, these systems are primarily symptom-based and detect diseases only after visible signs appear. They also lack integration with environmental monitoring systems and do not provide predictive capabilities for early disease prevention.

Based on these limitations and the real-world challenges observed, this research proposes an Early Disease Alerting System for rose plants. The system integrates environmental monitoring with early-stage disease detection by continuously measuring parameters such as temperature and humidity and identifying abnormal conditions that may lead to disease development. Additionally, threshold-based analysis of plant regions, such as leaves, is used to detect early signs of infection, while a simple machine learning classification model categorizes plant conditions into safe and dangerous zones. This enables the system to provide real-time alerts to farmers, allowing timely intervention before the disease spreads to other plants. Compared to existing approaches, the proposed system shifts from reactive disease detection to proactive disease prevention by combining environmental sensing, early symptom detection, and intelligent alerting.

In summary, the literature indicates that while significant progress has been made in disease identification using artificial intelligence, there remains a lack of integrated systems that combine environmental monitoring, early detection, and real-time alerting. The proposed Early Disease Alerting System addresses this gap by providing a comprehensive solution tailored to the challenges of rose cultivation in tropical environments such as Sri Lanka, thereby improving productivity and reducing crop losses.

Table 1: Summary of Existing Approaches and Limitations

Category	Approach	Strengths	Limitations
Traditional Farming	Manual monitoring & visual inspection [3], [4]	Simple and low cost	Late detection, depends on farmer experience
Greenhouse Cultivation	Shade control, misting, air drying [2]	Improves growth and yield	No real-time monitoring, manual control
Image Processing Systems	Leaf-based disease detection [6]	Detects visible diseases accurately	Only works after symptoms appear
Deep Learning Models	CNN-based classification (VGG, MobileNet) [7]	High accuracy (90%+)	No environmental data, reactive detection
Advanced AI Systems	Lightweight detection models (YOLO, KD) [8]	Real-time detection capability	Still symptom-based, no prediction
Disease Research Studies	Identification & management techniques [1], [3]	Strong biological knowledge	No automation or system implementation
<b>Proposed Work</b>	IoT + Threshold + ML Classification	Early detection + real-time alerts + predictive	Not applicable

The table summarizes the major existing approaches related to rose cultivation, disease detection, and smart agriculture systems, highlighting their strengths and limitations in comparison with the proposed Early Disease Alerting System. Traditional farming practices primarily rely on manual monitoring and visual inspection of plants, which are simple and cost-effective but highly dependent on farmer experience and often result in delayed disease detection, allowing infections to spread before intervention [3], [4]. Similarly, greenhouse-based cultivation techniques improve plant growth through environmental control mechanisms such as shading, misting, and air drying; however, these systems are typically manually operated and lack real-time monitoring capabilities, leading to inefficient responses to environmental fluctuations [2].

With the advancement of technology, image processing and machine learning-based approaches have been introduced for plant disease detection. These systems, including deep learning models such as Convolutional Neural Networks (CNNs), have demonstrated high accuracy in identifying diseases based on leaf images [6], [7]. In addition, advanced artificial intelligence techniques such as lightweight object detection models and knowledge distillation frameworks have improved real-time detection performance in field environments [8]. Despite these advancements, most of these systems are limited to symptom-based detection, meaning

they can only identify diseases after visible signs appear, and they do not incorporate environmental parameters for early prediction.

Furthermore, existing disease-related studies provide comprehensive knowledge regarding disease types, causes, and management strategies; however, they lack practical system implementations for real-time monitoring and early prevention [1], [3]. As a result, current solutions remain largely reactive rather than proactive.

In contrast, the proposed Early Disease Alerting System integrates IoT-based environmental monitoring with threshold-based detection and machine learning classification. The system continuously monitors environmental parameters such as temperature and humidity, detects abnormal conditions, and identifies early signs of disease before visible symptoms develop. By classifying plant conditions into safe and dangerous zones and providing real-time alerts to farmers, the system enables timely intervention and prevents disease spread. Therefore, the proposed approach effectively addresses the limitations of existing systems by shifting from reactive disease detection to predictive and preventive disease management.

## **1.2. Research Gap**

Despite the extensive research conducted in the domain of rose cultivation and plant disease detection, several limitations remain in existing approaches. Traditional farming practices rely heavily on manual monitoring and visual inspection of plants, which are highly dependent on farmer experience and often result in delayed identification of diseases [3], [4]. This delay allows diseases to spread rapidly across plants, leading to significant crop losses, particularly in greenhouse environments where conditions can accelerate disease development.

Greenhouse-based cultivation methods have been introduced to regulate environmental parameters such as temperature, humidity, and light intensity. While these techniques improve plant growth and yield, they are predominantly controlled manually and lack continuous monitoring capabilities [2]. As a result, farmers are unable to accurately detect real-time environmental fluctuations, which play a critical role in disease development. This limitation is particularly evident in tropical regions such as Sri Lanka, where temperature variations significantly impact plant health and productivity [2].

Therefore, the primary research gap lies in the lack of an integrated, real-time, and crop-specific nutrient management system that combines IoT-based environmental sensing with machine learning-driven prediction to provide adaptive and accurate fertilizer

recommendations for greenhouse rose cultivation. Recent advancements in image processing and machine learning have enabled automated disease detection systems. Deep learning models, including Convolutional Neural Networks (CNNs), have demonstrated high accuracy in identifying plant diseases based on leaf images [6], [7]. Furthermore, advanced techniques such as lightweight object detection models have improved real-time detection performance in field conditions [8]. However, these systems are primarily symptom-based and can only detect diseases after visible signs appear. They do not incorporate environmental data, nor do they provide predictive capabilities for early disease prevention.

Additionally, existing research on rose diseases provides comprehensive knowledge of disease types, causes, and management strategies, particularly emphasizing the role of environmental conditions in disease spread [1], [3]. However, these studies lack practical implementations of automated systems for continuous monitoring and early alerting. Consequently, current solutions remain reactive, focusing on disease detection and treatment rather than prevention.

A critical gap identified through both literature and real-world observations is the absence of integrated systems that combine environmental monitoring, early-stage disease detection, and real-time alerting. The case of a middle-scale Sri Lankan rose farmer further highlights this gap, where the lack of timely environmental insights and early disease identification led to uncontrolled disease spread and eventual discontinuation of cultivation. This demonstrates the need for a proactive system capable of identifying potential disease conditions before they become visible and spread across the farm.

Therefore, there is a clear need for an intelligent, IoT-based solution that continuously monitors environmental conditions, detects early indicators of disease using threshold-based analysis, and provides real-time alerts to farmers. Addressing this gap forms the foundation of the proposed Early Disease Alerting System, which aims to shift the paradigm from reactive disease detection to proactive disease prevention.

### 1.3. Research Problem

Rose cultivation is a highly sensitive agricultural practice that depends on precise environmental conditions such as temperature, humidity, and light intensity. In tropical countries like Sri Lanka, maintaining these optimal conditions is a significant challenge due to fluctuating weather patterns and high ambient temperatures [2]. As a result, rose plants are highly vulnerable to diseases, particularly fungal and viral infections, which can spread rapidly under favorable environmental conditions and lead to severe crop losses [3], [5].

Traditional rose cultivation practices primarily rely on manual monitoring and visual inspection of plant conditions. Farmers periodically observe plant leaves and environmental changes to make decisions regarding irrigation, shading, or disease control measures [4]. However, this approach is highly dependent on human judgment and lacks precision, often resulting in delayed detection of unfavorable conditions and disease onset. Studies have shown that many rose diseases, such as black spot and powdery mildew, develop rapidly under specific environmental conditions, and once visible symptoms appear, the infection has already progressed significantly [1], [3]. In some cases, such as Rose Rosette Disease, there is no effective cure, and the infection can lead to complete plant loss if not identified early [5].

Although greenhouse technologies have been introduced to regulate environmental conditions, these systems are largely controlled manually and do not provide continuous or real-time monitoring [2]. Farmers are therefore unable to accurately detect when critical environmental thresholds are exceeded, which directly contributes to plant stress and disease development. This limitation is further emphasized by real-world observations, where farmers rely on intermittent checks to assess temperature variations and manually activate systems such as misting or air drying. Such delayed interventions allow diseases to spread across flower beds before any corrective action can be taken.

Recent advancements in plant disease detection have focused on image processing and machine learning techniques. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated high accuracy in identifying diseases based on leaf images [6], [7]. Additionally, lightweight detection models have been proposed to improve real-time performance in field environments [8]. However, these approaches are inherently

reactive, as they depend on visible symptoms of disease. They do not incorporate environmental data or provide predictive capabilities for identifying disease risks before symptoms appear.

Furthermore, while existing research provides extensive knowledge on disease types, causes, and management strategies, there is a lack of integrated systems that combine environmental monitoring, early-stage disease detection, and real-time alerting mechanisms [1], [3]. This gap is particularly critical in middle-scale farming environments, where limited access to expert knowledge and technological tools increases the risk of crop failure.

Therefore, the core research problem can be identified as the absence of an intelligent and integrated system capable of continuously monitoring environmental conditions, detecting early-stage disease indicators, and providing real-time alerts to prevent disease spread in rose cultivation. Addressing this problem is essential to improve productivity, reduce crop losses, and support farmers in making timely and informed decisions.

## **1.4. Objectives**

### **1.4.1. Main Objectives**

The main objective of this research is to design and develop an intelligent Early Disease Alerting System for rose cultivation by integrating IoT-based environmental monitoring with threshold-based detection and machine learning classification. The system aims to continuously monitor critical environmental parameters such as temperature and humidity, identify abnormal conditions that may lead to disease development, and detect early-stage symptoms before visible damage occurs. By classifying plant conditions into safe and dangerous zones and providing real-time alerts to farmers, the proposed system seeks to enable proactive decision-making, reduce the spread of diseases, and improve overall productivity in rose cultivation. This approach addresses the limitations of existing systems, which primarily focus on reactive disease detection rather than early prediction and prevention [2], [6], [8].

#### **1.4.2. Specific Objectives**

- To analyze the environmental factors (temperature, humidity, and light conditions) that influence rose plant health and disease development based on existing studies [2], [3].
- To design and implement an IoT-based system for real-time monitoring of greenhouse environmental conditions.
- To develop a threshold-based detection mechanism to identify abnormal environmental conditions and early signs of plant disease.
- To apply a machine learning classification model to categorize plant conditions into safe and dangerous zones based on detected patterns.
- To design a real-time alerting mechanism to notify farmers of potential disease risks and environmental abnormalities.
- To evaluate the effectiveness of the proposed system in preventing disease spread compared to traditional and existing technology-based approaches [6], [7].
- To provide a cost-effective and practical solution suitable for middle-scale rose farmers in Sri Lanka.

#### **1.5. Novelty and Contribution of the Study**

The proposed Early Disease Alerting System introduces a novel approach to rose plant disease management by integrating environmental monitoring, threshold-based early detection, and machine learning classification into a single unified framework. While existing studies have focused primarily on disease identification using image processing and deep learning techniques, these approaches are largely reactive, as they detect diseases only after visible symptoms appear on plant leaves [6], [7]. In contrast, this research emphasizes early-stage detection by identifying abnormal environmental conditions and subtle indicators of disease development before the symptoms become visually apparent.

A key novelty of this study lies in the integration of IoT-based real-time environmental monitoring with threshold-driven analysis. Previous research has established that environmental factors such as temperature, humidity, and light intensity play a critical role in disease development [2], [3]; however, these parameters have not been effectively incorporated into automated disease alerting systems. The proposed system continuously

monitors these environmental conditions and compares them against predefined thresholds to identify potential risk situations, enabling proactive intervention.

Another significant contribution of this research is the use of a simple yet effective machine learning classification model to categorize plant conditions into safe and dangerous zones. Unlike complex deep learning models that require large datasets and computational resources, the proposed approach is designed to be lightweight and practical for real-world deployment in middle-scale farming environments. This makes the system more accessible and cost-effective for farmers, particularly in developing regions such as Sri Lanka.

Furthermore, the system introduces a real-time alerting mechanism that directly supports farmer decision-making. Existing solutions often lack actionable outputs, whereas this system provides immediate notifications when environmental conditions exceed safe limits or when early signs of disease are detected. This feature significantly reduces response time and helps prevent the spread of diseases across plants.

In addition, this study incorporates real-world insights obtained from a middle-scale Sri Lankan rose farmer, ensuring that the proposed solution addresses practical challenges faced in actual cultivation environments. The integration of empirical observations with technical design enhances the applicability and relevance of the system.

Overall, the main contributions of this study can be summarized as follows:

- Introduction of a proactive disease management approach that focuses on early detection rather than post-symptom identification.
- Integration of IoT-based environmental monitoring with threshold-based analysis for real-time risk detection.
- Development of a lightweight machine learning classification model for identifying safe and dangerous plant conditions.
- Implementation of a real-time alerting system to support timely farmer intervention.
- Provision of a cost-effective and practical solution tailored for middle-scale rose cultivation in tropical regions.

## **2. METHODOLOGY**

### **2.1. System Overview**

The proposed Early Disease Alerting System is designed as a portable, IoT-enabled device to monitor environmental conditions and detect early-stage disease risks in rose plants. The system is implemented as a handheld stick device equipped with temperature and humidity sensors, a microcontroller, and a user interface. The device enables farmers to manually initiate readings by pressing a button, making it practical for field-level deployment.

The system utilizes two primary sensors: the MLX90614 infrared temperature sensor to measure leaf (plant) temperature and the SHT31 sensor to measure ambient air temperature and humidity. These parameters are critical for identifying environmental conditions that contribute to disease development, as established in previous studies [2], [3]. The collected sensor data is transmitted via an ESP32 microcontroller and stored in a cloud-based MongoDB database for further analysis.

A machine learning model is trained using collected sensor data to classify plant conditions into safe and dangerous zones. The system calculates a temperature difference parameter ( $\Delta T$ ), defined as the difference between plant temperature and air temperature, which serves as a key indicator of plant stress and disease risk. Based on the model predictions, real-time alerts are provided to farmers through a mobile application, enabling timely intervention.

The physical prototype of the system, including sensors, processing unit, and interface components, is illustrated in Fig. 2.1–2.3.

### **2.2. System Architecture**

The overall system architecture consists of four main components: data acquisition, data storage, machine learning processing, and user interaction.

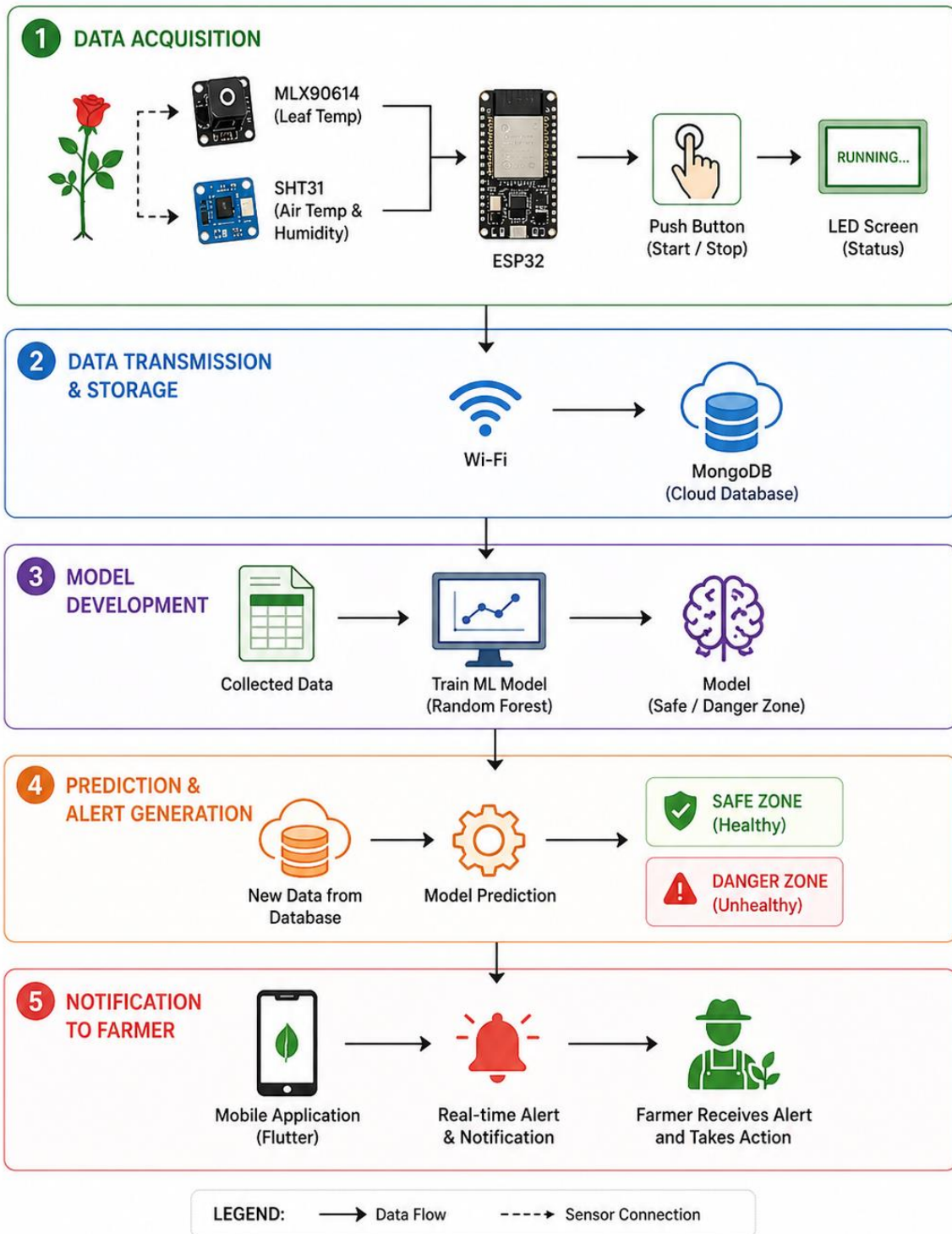


Figure 1: System Architecture Diagram

The architecture begins with the sensor layer, where environmental data is collected. The ESP32 microcontroller processes and transmits this data to a MongoDB database. The stored data is then analyzed using a machine learning model, and the results are delivered to the farmer via a mobile application.

### 2.2.1. Data Acquisition Layer:

The Data Acquisition Layer is responsible for collecting real-time environmental and plant-specific data using the handheld device. This layer consists of two primary sensors: the MLX90614 infrared sensor, which measures the leaf (plant) temperature, and the SHT31 sensor, which captures ambient air temperature and humidity. These parameters are essential for identifying environmental conditions that influence plant health and disease development [2], [3].

The sensors are interfaced with an ESP32 microcontroller, which acts as the processing unit. The device includes a push button that allows the user to initiate or stop data collection, ensuring ease of use in field conditions. Additionally, an LED screen is used to display the operational status of the device. The collected sensor readings are processed locally and prepared for transmission to the cloud. This layer ensures accurate and timely data collection, which forms the foundation for subsequent analysis.

### 2.2.2. Data Transmission and Storage Layer:

The Data Transmission and Storage Layer facilitates the transfer of collected data from the device to a cloud-based database. The ESP32 microcontroller uses Wi-Fi connectivity to transmit sensor readings to a MongoDB database. Each data entry is stored with a timestamp, allowing for temporal analysis of environmental conditions. The use of a cloud database enables centralized storage, scalability, and easy access to historical data. This is particularly important for training machine learning models and analyzing long-term trends in plant health. The availability of structured and continuous data improves the reliability of the system and supports real-time processing.

### 2.2.3. Model Development Layer:

The Model Development Layer is responsible for analyzing collected data and building a predictive model for plant health classification. In this study, a Random Forest Classifier is used due to its robustness and effectiveness in handling environmental datasets.

The model is trained using features such as air temperature, plant temperature, humidity, temperature difference ( $\Delta T$ ), time of day, and day/night classification. The

temperature difference is calculated as the difference between plant temperature and air temperature, serving as a key indicator of plant stress conditions.

Data preprocessing steps include cleaning, feature engineering, and labeling based on domain-specific rules. The dataset is split into training and testing subsets, and the model is evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The trained model is capable of identifying patterns associated with healthy and unhealthy plant conditions.

#### 2.2.4. Prediction and Alert Generation Layer:

The Prediction and Alert Generation Layer utilizes the trained machine learning model to analyze new incoming data from the database. Based on the input parameters, the model classifies the plant condition into one of two categories: Safe Zone (healthy) or Danger Zone (unhealthy).

If the system detects abnormal environmental conditions or early indicators of disease, it generates an alert. This proactive approach allows for early intervention before visible symptoms appear, addressing the limitations of traditional and image-based detection methods, which are primarily reactive [6], [8].

This layer plays a critical role in transforming raw data into actionable insights, enabling effective disease prevention.

#### 2.2.5. Notification Layer:

The Notification Layer is responsible for delivering the system's output to the end user. A mobile application developed using Flutter is used to provide real-time alerts and status updates to farmers. When a dangerous condition is detected, the system sends an immediate notification to the farmer, enabling timely corrective actions such as adjusting greenhouse conditions.

The mobile application also displays current sensor readings and plant health status, providing a user-friendly interface for monitoring. This layer ensures that the system's insights are effectively communicated to the farmer, supporting informed decision-making and reducing the risk of disease spread.

### **2.3. Data Collection and Preprocessing**

Data collection is performed using the developed handheld device by capturing real-time environmental readings from rose plants. The dataset consists of parameters such as air temperature, plant temperature, humidity, time of day, and calculated temperature difference. Data was collected over multiple days across different plants to ensure variability and reliability.

A key parameter used in this study is the temperature difference ( $\Delta T$ ), calculated as:

$$\Delta T = \text{Plant Temperature} - \text{Air Temperature}$$

This parameter helps identify plant stress conditions, as abnormal temperature differences indicate potential disease risks.

The collected dataset is stored in CSV format and includes additional features such as hour and day/night classification. Data preprocessing involves cleaning missing values, formatting time-based features, and labeling plant health conditions using domain-specific rules. For example, during daytime, plants are considered healthy if  $\Delta T$  is within a specific range and air temperature remains below a threshold. During nighttime, high humidity combined with negative temperature differences indicates a risk of fungal infection.

### **2.4. Model Development and Recommendation System**

A supervised machine learning approach is used to classify plant conditions into healthy and unhealthy categories. The Random Forest Classifier is selected due to its robustness and ability to handle non-linear relationships in environmental data.

The model is trained using features such as:

- Air temperature
- Plant temperature
- Humidity
- Temperature difference ( $\Delta T$ )
- Hour of the day
- Day/night indicator

using accuracy, precision, recall, and F1-score metrics. The trained model achieved high classification accuracy, indicating its effectiveness in identifying disease-prone conditions.

The prediction output is categorized as:

- Safe Zone (Healthy)
- Danger Zone (Unhealthy – Attention Needed)

Based on the prediction, the system generates recommendations and alerts for the farmer. If a dangerous condition is detected, the farmer is notified via the mobile application to take corrective actions such as adjusting humidity or temperature control mechanisms.

## 2.5. System Implementation Technologies

The system is implemented using a combination of hardware and software technologies:

### Hardware Components

- **MLX90614 Sensor** – Measures leaf temperature
- **SHT31 Sensor** – Measures air temperature and humidity
- **ESP32 Microcontroller** – Handles data processing and communication
- **Push Button** – Initiates sensor readings
- **LED Display** – Displays device status

### Software Technologies

- **Python** – Data processing and machine learning model development
- **Scikit-learn** – Implementation of Random Forest Classifier
- **MongoDB** – Cloud database for storing sensor data
- **Flutter** – Mobile application for real-time alerts
- **Joblib** – Model serialization and deployment

The integration of these technologies enables real-time monitoring, efficient data processing, and seamless communication between the device and the user.

## **2.6. Commercialization aspect of the product**

### **2.6.1. Product Overview and Value Proposition**

The proposed Early Disease Alerting System is designed not only as a research prototype but also as a commercially viable smart agriculture solution tailored for middle-scale rose farmers. The system is developed as a portable, handheld device integrated with IoT and machine learning capabilities, enabling real-time environmental monitoring and early disease detection. Unlike traditional greenhouse management practices that rely on manual observation, this product provides automated, data-driven insights to support timely and informed decision-making.

The product consists of a sensor-based stick device equipped with MLX90614 and SHT31 sensors to measure plant temperature, air temperature, and humidity. These readings are processed through an ESP32 microcontroller and transmitted to a cloud-based database, where a trained machine learning model analyzes the data to identify plant health conditions. The results are then communicated to the farmer via a mobile application, providing real-time alerts and recommendations.

The key value proposition of this product lies in its ability to shift disease management from a reactive approach to a proactive one. Existing solutions in agriculture primarily focus on detecting diseases after visible symptoms appear, which often results in delayed intervention and increased crop loss [6], [7]. In contrast, the proposed system identifies early-stage environmental anomalies and potential disease risks before symptoms become visible, enabling preventive action. This significantly reduces the likelihood of disease spread across plants and improves overall farm productivity.

Furthermore, the product is designed to be cost-effective, user-friendly, and suitable for real-world deployment in developing regions such as Sri Lanka. The handheld design allows farmers to easily operate the device within greenhouse environments, while the push-button functionality simplifies the data collection process. The integration with a mobile application ensures accessibility and convenience, even for users with limited technical expertise.

Another important aspect of the product is its adaptability and scalability. The system can be extended to support additional sensors, larger datasets, and more advanced predictive models, making it applicable not only to rose cultivation but also to other

crops. This flexibility enhances its commercial potential in the broader smart agriculture market.

In summary, the proposed Early Disease Alerting System offers a unique combination of affordability, portability, and intelligent decision support. By addressing the critical challenges of early disease detection and real-time environmental monitoring, the product provides significant value to farmers and contributes to improving agricultural efficiency and sustainability.

### **2.6.2. Business Model and Target Market**

The proposed Early Disease Alerting System is designed to be a commercially viable solution within the smart agriculture domain, particularly targeting middle-scale farmers who require cost-effective and practical tools for crop monitoring and disease prevention. The business model is centered around a combination of hardware sales and value-added digital services, enabling both immediate usability and long-term scalability.

The primary component of the business model is the sale of the handheld sensor device, which includes the MLX90614 and SHT31 sensors, ESP32 microcontroller, and user interface components. This device is designed to be affordable and durable, making it suitable for farmers operating in resource-constrained environments. In addition to the hardware, the system includes a mobile application that provides real-time monitoring and alerting services. A freemium or subscription-based model can be adopted for advanced features such as historical data analytics, predictive insights, and extended cloud storage.

The target market for this product primarily includes middle-scale rose farmers in Sri Lanka, particularly those operating in greenhouse environments where environmental conditions need to be carefully managed. These farmers often face challenges related to disease spread, lack of real-time monitoring, and limited access to expert knowledge. The proposed system directly addresses these issues by providing early warnings and actionable insights, making it highly relevant to this segment.

In addition to the primary market, the product has the potential to expand into broader agricultural sectors. The system can be adapted for other high-value crops that are

sensitive to environmental conditions, such as vegetables, fruits, and ornamental plants. This scalability increases the commercial potential of the product and allows it to penetrate both local and international markets.

From a value delivery perspective, the system reduces crop losses, improves productivity, and minimizes the need for manual monitoring. These benefits translate into economic gains for farmers, making the product a compelling investment. Furthermore, the integration of IoT and machine learning technologies aligns with the global trend toward smart agriculture, enhancing the product's competitiveness in the market.

In summary, the business model combines affordable hardware with scalable digital services, while the target market focuses on middle-scale farmers and greenhouse operators. The adaptability of the system to other crops and regions further strengthens its commercial viability and long-term growth potential.

### **2.6.3. Feasibility and Scalability**

The feasibility of the proposed Early Disease Alerting System is supported by its use of low-cost, readily available hardware components and widely adopted software technologies. The system is built using sensors such as MLX90614 and SHT31, along with an ESP32 microcontroller, all of which are affordable and easily accessible in the market. This ensures that the overall cost of the device remains low, making it suitable for middle-scale farmers in developing regions such as Sri Lanka. Additionally, the handheld design of the device enhances its practicality, allowing farmers to easily operate it within greenhouse environments without requiring specialized technical skills.

From a technical perspective, the system leverages established technologies such as Wi-Fi communication, cloud-based databases (MongoDB), and machine learning frameworks (Scikit-learn), which are reliable and well-supported. The implementation of a Random Forest classification model further contributes to feasibility, as it provides accurate predictions while requiring relatively low computational resources compared to more complex deep learning models [6], [7]. The use of a Flutter-based mobile application also ensures cross-platform compatibility, enabling farmers to access the system using common smartphones.

The system's feasibility is further strengthened by its alignment with real-world agricultural practices. The incorporation of a push-button mechanism for data collection simplifies user interaction, while the real-time alerting feature addresses a critical need identified through farmer feedback. By directly targeting existing challenges such as delayed decision-making and lack of environmental monitoring, the system demonstrates practical applicability in real farming environments.

In terms of scalability, the proposed system is designed to support expansion across multiple dimensions. Firstly, the cloud-based architecture allows for the storage and management of large volumes of sensor data, enabling the system to scale across multiple devices and farms. This makes it possible to deploy the system in larger agricultural setups without significant modifications.

Secondly, the modular design of the system allows for the integration of additional sensors, such as soil moisture or light intensity sensors, to enhance functionality. This flexibility enables the system to adapt to different crop types and agricultural conditions, extending its applicability beyond rose cultivation.

Thirdly, the machine learning model can be continuously improved by incorporating larger and more diverse datasets collected from different environments. This will enhance prediction accuracy and enable the development of more advanced predictive features, such as disease forecasting and automated recommendations.

Finally, the mobile application and cloud infrastructure support remote access and centralized management, making it possible to deploy the system in geographically distributed locations. This opens opportunities for large-scale adoption in both local and international markets.

In summary, the proposed Early Disease Alerting System is both technically and economically feasible, with strong potential for scalability. Its low-cost design, practical implementation, and flexible architecture make it a viable solution for improving disease management in agriculture, while its ability to expand across different crops and regions enhances its long-term commercial potential.

## 2.7. Implementation And Testing

### 2.7.1. System Implementation and Workflow

The implementation of the proposed Early Disease Alerting System involves the integration of hardware, software, and machine learning components to enable real-time environmental monitoring and early disease detection. The system is developed as a handheld IoT device combined with a cloud-based processing framework and a mobile application interface.

The hardware implementation consists of an ESP32 microcontroller interfaced with two sensors: the MLX90614 infrared sensor for measuring plant (leaf) temperature and the SHT31 sensor for measuring ambient air temperature and humidity. These sensors are mounted on a portable stick-like device, allowing farmers to easily collect readings directly from plants. A push-button mechanism is incorporated to control the start and stop of data collection, ensuring ease of use in practical farming environments.

The workflow of the system begins with data acquisition from the sensors when the user activates the device. The ESP32 microcontroller reads the sensor values and processes them locally. The collected data includes plant temperature, air temperature, and humidity. These readings are then transmitted via Wi-Fi to a cloud-based MongoDB database, where they are stored with corresponding timestamps for further analysis.

Once the data is stored, preprocessing is performed to derive additional features required for machine learning analysis. A key parameter used in this system is the temperature difference ( $\Delta T$ ), calculated as the difference between plant temperature and air temperature. This parameter is critical for identifying plant stress and potential disease conditions. Additional features such as time of day and day/night classification are also incorporated to improve model accuracy.

The machine learning model, implemented using a Random Forest Classifier, is trained using a labeled dataset collected from multiple plants over several days. The dataset includes features such as air temperature, plant temperature, humidity, temperature difference, and temporal attributes. A rule-based labeling function is used to classify data into healthy and unhealthy categories based on environmental thresholds. For example, during daytime, a plant is considered healthy if the temperature difference remains within a defined range and air temperature does not exceed a specified limit. During nighttime, high humidity combined with negative temperature differences indicates a potential fungal risk condition.

The dataset is divided into training and testing subsets, and the model is trained using an ensemble of decision trees to improve classification performance. The trained model is then used to predict plant health status for new incoming data. The prediction output is categorized into two states: Safe Zone (healthy) and Danger Zone (unhealthy).

The final stage of the workflow involves delivering the prediction results to the end user. A mobile application developed using Flutter is used to display real-time plant

health status and sensor readings. When a dangerous condition is detected, the system generates an alert notification, allowing the farmer to take immediate corrective actions such as adjusting temperature or humidity levels.

Overall, the system workflow follows a structured pipeline consisting of data acquisition, transmission, preprocessing, model prediction, and user notification. This integrated approach ensures that environmental changes are continuously monitored and analyzed, enabling early detection of disease risks and timely intervention. By combining IoT technology with machine learning, the system provides a practical and effective solution for improving disease management in rose cultivation.

### **2.7.2. Testing and Evaluation**

To evaluate the performance, reliability, and robustness of the proposed Early Disease Alerting System, both functional testing and machine learning model evaluation were conducted under various operating conditions. The objective of this evaluation was to ensure that the system performs accurately under normal, abnormal, and edge-case environmental scenarios while providing consistent and reliable outputs.

Functional testing was carried out to validate the behavior of the system across different input scenarios, including normal environmental conditions, missing sensor data, and extreme environmental variations. These tests were designed to verify the correctness of data acquisition, transmission, processing, and alert generation components. Additionally, the integration between the hardware device, cloud database, machine learning model, and mobile application was tested to ensure seamless end-to-end operation.

The machine learning model was evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score. The dataset collected from multiple plants over several days was divided into training and testing subsets using an 80:20 ratio. The Random Forest Classifier demonstrated high classification accuracy, indicating its effectiveness in distinguishing between safe and dangerous environmental conditions.

Table 2.1 summarizes the functional testing results of the proposed system.

Table 2: Functional Testing Results

Test Case ID	Input Scenario	Expected Outcome	Actual Outcome	Status
TC01	Valid sensor data (normal range)	Accurate classification of plant health (Safe Zone)	Model correctly classified plant condition with high accuracy	Pass
TC02	Missing sensor values	System handles missing data without failure	Missing values handled during preprocessing without system crash	Pass
TC03	Extreme environmental conditions (high temp / humidity)	Detection of abnormal condition and alert generation	Model successfully classified as Danger Zone and triggered alert	Pass
TC04	Nighttime high humidity with low $\Delta T$	Detection of fungal risk condition	System correctly identified risk and generated warning	Pass
TC05	Continuous real-time data flow	Stable system performance without delay	Data successfully transmitted and processed in real-time	Pass
TC06	Device button operation (start/stop)	Controlled data acquisition	Controlled data acquisition	Pass

The results demonstrate that the system performs reliably under different environmental conditions and input scenarios. The machine learning model effectively identifies patterns associated with plant health and provides accurate predictions. Furthermore, the system successfully generates real-time alerts when abnormal conditions are detected, enabling timely intervention by the farmer.

Overall, the testing and evaluation confirm that the proposed Early Disease Alerting System is robust, accurate, and suitable for practical deployment in real-world agricultural environments. The combination of IoT-based monitoring and machine learning-based prediction ensures improved reliability compared to traditional and existing approaches.

### 3. RESULTS AND DISCUSSION

#### 3.1. Results and Discussion

The proposed Early Disease Alerting System was evaluated based on its ability to accurately monitor environmental conditions, classify plant health status, and provide real-time alerts to the user. The system successfully integrated hardware, cloud infrastructure, and machine learning components to deliver end-to-end functionality.

The Random Forest Classifier model was trained using the collected dataset consisting of environmental parameters such as air temperature, plant temperature, humidity, temperature difference ( $\Delta T$ ), and temporal features. The model achieved high classification accuracy when distinguishing between safe and dangerous plant conditions. The evaluation metrics, including precision, recall, and F1-score, indicate that the model performs reliably in identifying early-stage disease risk conditions.

One of the key observations from the results is the effectiveness of the temperature difference parameter ( $\Delta T$ ) in identifying plant stress conditions. It was observed that abnormal variations in  $\Delta T$ , combined with high humidity levels, significantly contributed to the classification of dangerous conditions. This supports findings from previous studies, which highlight the influence of environmental factors on disease development [2], [3].

The system also demonstrated reliable real-time performance. Sensor data collected through the handheld device was successfully transmitted to the MongoDB database and processed by the machine learning model without significant delay. The mobile application provided instant feedback to the user, displaying plant health status and generating alerts when necessary.

Compared to traditional and existing systems, the proposed solution offers a proactive approach by identifying potential disease risks before visible symptoms appear. This significantly reduces the likelihood of disease spread and improves overall farm management. The results confirm that integrating IoT-based monitoring with machine learning classification enhances the effectiveness of disease prevention strategies.

### **3.2. Limitations and Future Work**

Despite the effectiveness of the proposed system, several limitations were identified during the implementation and testing phases.

Firstly, the machine learning model was trained using a relatively small dataset collected over a limited time period. While the model achieved satisfactory performance, a larger and more diverse dataset would improve its generalization capability and prediction accuracy.

Secondly, the system currently focuses on a limited set of environmental parameters, namely temperature and humidity. Other factors such as soil moisture, light intensity, and nutrient levels, which also influence plant health, are not included in the current implementation.

Thirdly, the threshold-based labeling approach used for training the model is based on predefined rules, which may not capture all possible variations in plant behavior under different environmental conditions.

Additionally, the system requires manual interaction through a handheld device to collect data. Finally, the author conducted system testing, evaluation, and documentation of the entire project, including analysis of results and identification of research gaps. This comprehensive involvement demonstrates the author's contribution to both the technical and practical aspects of the system.

Future work can address these limitations by expanding the dataset, incorporating additional sensors, and exploring advanced machine learning or deep learning models for improved prediction. The system can also be extended to support continuous monitoring and automated control mechanisms, such as activating misting or ventilation systems based on detected conditions. Furthermore, integrating advanced analytics and recommendation systems into the mobile application can provide more detailed guidance to farmers.

### **3.3. Individual Contribution**

The development of the Early Disease Alerting System was carried out as an individual contribution, focusing on the design, implementation, and evaluation of the system.

The author was responsible for designing the overall system architecture, including the integration of hardware components, cloud infrastructure, and machine learning modules. The handheld device was developed using an ESP32 microcontroller and sensors (MLX90614 and SHT31) to collect environmental data.

The author also performed data collection, preprocessing, and dataset preparation, including feature engineering and labeling based on domain-specific rules. The machine learning model was developed and trained using Python and Scikit-learn, with a focus on achieving accurate classification of plant health conditions.

In addition, the author developed the mobile application using Flutter to provide real-time alerts and user interaction. The integration between the hardware device, cloud database, machine learning model, and mobile application was implemented and tested by the author.

## **4. CONCLUSION**

This research presented the design and implementation of an Early Disease Alerting System for rose plants, aimed at addressing the challenges of environmental monitoring and disease prevention in agriculture. The system integrates IoT-based sensing, cloud data storage, and machine learning techniques to provide a comprehensive solution for early detection of disease-prone conditions.

The results demonstrate that the system is capable of accurately monitoring environmental parameters and classifying plant health status into safe and dangerous zones. The use of temperature difference ( $\Delta T$ ) as a key feature proved effective in identifying plant stress conditions. Additionally, the real-time alerting mechanism enables farmers to take timely action, reducing the risk of disease spread and improving crop productivity.

The study also highlights the limitations of existing approaches, which primarily focus on reactive disease detection based on visible symptoms. By shifting toward a proactive approach,

the proposed system contributes to advancing smart agriculture practices and improving decision-making in farming.

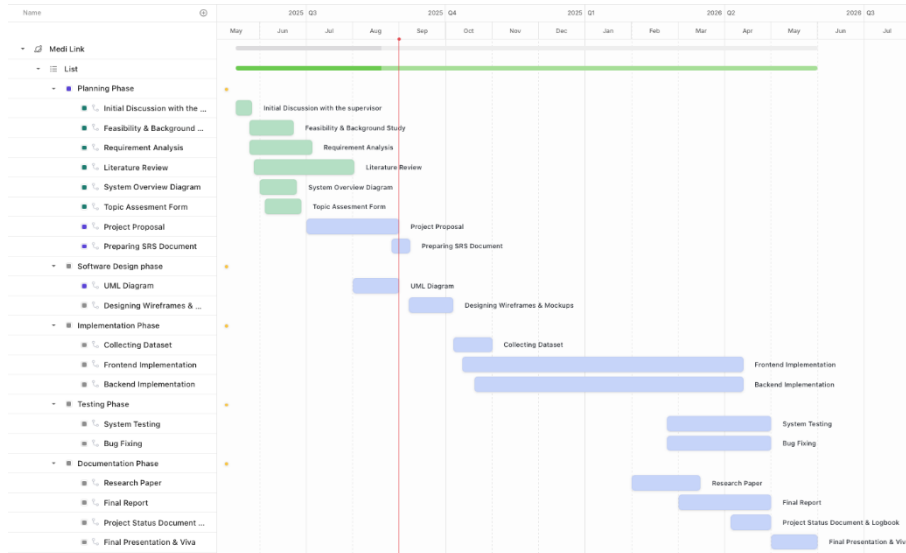
Overall, the Early Disease Alerting System provides a practical, cost-effective, and scalable solution for middle-scale farmers, particularly in tropical regions such as Sri Lanka. With further improvements and enhancements, the system has the potential to be widely adopted and applied to various crops, contributing to sustainable agricultural development.

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## 6. APPENDICES

### 6.1. Appendix A: Gantt Chart



Appendix A: Gantt Chart